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ABSTRACT

Erasmus Program and Labor Market Outcomes: Evidence from a Fuzzy Regression Discontinuity Design

We study the impact that participation in the Erasmus program produces on a number of labor market outcomes. By implementing a Fuzzy Regression Discontinuity Design, we show that participating in the international mobility program positively affects the probability of being employed three years after graduation and reduces the time spent to find a job, whereas no significant effect is found on the likelihood of getting a job in line with the qualification acquired. These results are mainly driven by male and STEM graduates. We further investigate potential mechanisms underlying our results and find that spending a period of time studying abroad improves both the proficiency in spoken English and graduates' academic performance, and tends to increase the willingness to move to find a job.

JEL Classification: C26, D04, I23, I26, J00

Keywords: international mobility, Erasmus, academic outcomes, employment, Fuzzy Regression Discontinuity Design

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1 Introduction

Promoting international student mobility is a key feature of the European higher education policy that aims to strengthen intra-community cooperation, facilitate European integration and create a common labor market. The Erasmus mobility project—one of the oldest and most popular policies financed by the European Union—has involved around ten million students wishing to experience living abroad, improve their language skills and enhance their employment prospects (European Commission, 2020). Thanks to the additional resources devoted by the European Commission to the 2021–2027 Erasmus+ program, the number of university students spending time abroad during their studies will presumably become even greater in the future (European Commission, 2022).

International mobility—together with the social returns from the promotion of common European values, social integration, intercultural understanding and a sense of belonging to a community—is expected to generate a number of private returns including better labor market outcomes. From a theoretical point of view, the effect of mobility on professional outcomes can be related both to human capital acquisition and signaling. Students who spend time abroad can learn a new language and acquire a number of soft skills, such as independence, adaptability and so on. They might also improve their human capital through access to higher education institutions of better quality. In addition, this experience can affect students' propensity to migrate and then boost, via this channel, both the likelihood of finding a job and the probability of attaining a position that suits their qualifications (Kratz and Netz, 2018). Instead, a negative effect might occur if students living abroad put less effort into their study activities (because of adaptation costs or greater involvement in entertainment activities), leading to a detrimental impact on academic performance (Relyea et al., 2008). It could also be true that some of the knowledge acquired when studying abroad is not useful in students' home country labor market. As regards signaling, individuals who gained international experience by living abroad during their educational process might be more attractive for employers as they are presumably more adaptive, more motivated and more open to new experiences.

However, mainly due to identification issues, evidence provided by the empirical literature is far from conclusive, with some papers showing positive effects (Di Pietro, 2022; d'Hombres and Schnepf, 2021), while others find no impact on different labor market outcomes (Koda and Yuki, 2013; Messer and Wolter, 2007; Pinto, 2022; Wiers-Jenssen, 2011). We contribute to this literature by analyzing how international mobility influences labor market outcomes of students enrolled at a large Italian university. We take advantage of a unique dataset combining administrative data on all the applications for the Erasmus grants available at the University of Calabria with information on students' academic careers and graduates' employment status from AlmaLaurea annual surveys.[1]

In order to overcome problems deriving from selection of students in the Erasmus program, we adopt a Fuzzy Regression Discontinuity Design, so exploiting the fact that each year the available grants for the program are assigned to students with a position above a certain threshold in a specific ranking based on the average grade obtained at exams passed and on the number of credits acquired, weighted by years of study. Due to imperfect compliance, being above or below the cut-off does not precisely determine the treatment status and, therefore, we use a Fuzzy Regression Discontinuity Design (i.e., an instrumental variable approach), where the effective participation in the program is instrumented by using the exogenous assignment to the treatment.

The assigned treatment strongly correlates with the effective treatment: being assigned to the treatment around the threshold leads to an increase in the probability of studying abroad through the Erasmus program of about 50–53 percentage points.

Our 2SLS estimation results show a positive and statistically significant effect of participating in the program on the probability of finding employment. We also find that international mobility reduces the time spent by students to find a job after graduation, while no effect is found on the probability of getting a job in line with their field of study. These effects are mainly driven by male and STEM graduates and are larger in terms of magnitude for those who spent a period of study in an institution of relatively higher quality.

The richness of our data also allows us to inquire about a number of different channels, such as improvement in language skills, in academic performance and in mobility propensity. We find that the positive effects detected in our study stem from an improvement in students' proficiency in spoken English and from a better academic performance, since spending a period of time studying abroad positively affects (especially for male and STEM students) both the graduation mark and the probability of graduating with honors.

Our work complements the growing research which analyzes the impact of international mobility on individual professional and personal outcomes. While the literature examining the relationship between international mobility and labor market outcomes is quite extensive (see Di Pietro, 2022,

[1] AlmaLaurea is an Italian Interuniversity Consortium of 78 member universities administering annual surveys regarding the characteristics and performance of graduates who obtained their Degrees at these universities (about 90% of graduates are interviewed each year).

for a survey), the papers trying to identify a causal impact are scant. Individuals who participate in international mobility programs often have peculiar qualities (Messer and Wolter, 2007; Di Pietro, 2022), which are also likely to affect their labor market performance, so leading to an endogeneity problem that produces biased estimates.

The few existing papers that have addressed this issue rely mainly on an instrumental variable approach.[2] Parey and Waldinger (2011) exploit department level variations in international student exchange programs to analyze whether studying abroad increases the probability of working abroad for German university graduates. Their results show a large and positive impact. A similar approach is used by Di Pietro (2012; 2015), who uses Italian data and considers as an instrument the proportion of students who participated in international exchange programs from within the same department (a proxy for students' exposure to international exchange programs). He finds that international mobility leads to an improvement in the probability of being employed three years after graduation and increases the probability of working abroad. Pinto (2022) also uses an instrumental variable strategy, based on the supply of Erasmus scholarships by area of study and region of residence, and shows that international mobility positively affects the probability of working in a foreign country, while no effect is found on employment probability.

Nevertheless, these studies might suffer from an upward bias as those students who choose departments characterized by high international mobility might differ from other students and have a higher mobility propensity. In order to address this issue, we adopt the same identification strategy as Oosterbeek and Webbink (2006) and Granato et al. (2022), who apply a Fuzzy Regression Discontinuity Design to control for unobserved heterogeneity between treated and control students. Granato et al. (2022) consider students enrolled at the University of Bologna and explore the effects of the Erasmus program on students' academic performance, finding a positive impact on their final graduation mark and average grades before graduation. Oosterbeek and Webbink (2006) use data on talented Dutch university students and analyze the impact of studying abroad on the probability of living in a foreign country. They find that student mobility induces a brain drain with an increase of about 50 percentage points in the probability of working abroad.

Compared to these studies, our analysis differs in several respects. First, we are able to conduct a RDD analysis by relating participation in the Erasmus program with labor market outcomes

[2] A number of studies have, instead, relied on different propensity score matching models. See, among others, Rodrigues (2013), Jacob et al. (2019), Liwiński (2019), d'Hombres and Schnepf (2021), Iriondo (2020) and Netz and Grüttner (2021). These studies do not control for unobserved selection bias and may, thus, provide biased estimates.

three years after graduation (employment probability, time spent to find a job and type of job). Second, thanks to the richness of our data, we can analyze heterogeneous effects of students' international mobility across different dimensions, i.e. field of study, time spent abroad, degree level and quality of academic institutions. Furthermore, we investigate possible mechanisms at play that drive our results through an investigation of the impact of interest on graduation grade, time taken to graduate and proficiency in the English language. Last but not least, we consider students from a large public university located in an economically disadvantaged region of Italy, characterized by the highest rate of unemployment in the EU. This may be particularly interesting from the perspective of labor market analysis, as existing studies mainly focus on developed areas and tight labor markets.

The rest of the paper is organized as follows. In Section 2, we present the key features of the Erasmus program and describe the data used in the study. Section 3 describes the empirical strategy and a number of validity checks. Our main results are reported in Section 4, while, in Section 5, we present Intention-To-Treat effects. The discussion of candidate mechanisms that might explain our findings is presented in Section 6. Section 7 concludes.

2 Institutional setting and data description

2.1 The Erasmus program

The University of Calabria (UniCal hereafter) is a large public university situated in the South of Italy, with about 24,500 students enrolled in 80 different degree courses. It officially joined the Erasmus program in 1997 and since then the number of students participating in the program has increased every year.[3]

In February of each year, UniCal publishes a call for applications (expiring after one month) to take part in the Erasmus program in the following academic year. The number of grants provided is determined on the basis of the Erasmus funds that are allocated to UniCal by the Italian National Erasmus Agency. In turn, UniCal allocates the available grants to the departments[4] according to the number of students effectively involved in the program in the past academic year. Getting the grant is a necessary condition for entering the program and studying abroad at a host university, which has previously signed a student exchange agreement with UniCal.

The admission criteria are established by the International Committee at UniCal and are based

[3]The intensification of internationalization is among the main objectives of a university development strategy that is constantly monitored to guarantee high student participation in international exchange programs.

[4]The department is an administrative division of the university devoted to a particular academic discipline.

on students' academic performances. More precisely, each applying student is assigned a score that depends on the average of all grades and on the number of acquired credits, weighted by the year of study. Any student enrolled at UniCal may apply for the call, regardless of his/her nationality and level of study (Bachelor or Master's Degree) as long as they satisfy the minimum requirements in terms of credits and grades.

The selection procedure concludes with the release of a list of applicants for each department, usually published in April. Applicants are ranked according to their score and the available grants are assigned to the highest-ranked students, given the number of scholarships assigned to each department. After the publication of rankings, students have approximately one week to decide whether or not to accept the grant. The mobility grants assigned to students who do not accept the offer are re-allocated to the following applicants in the ranking. If some slots remain vacant after this process, it will no longer be possible to reassign the remaining grants to any student.

Students obtaining the grant may stay abroad from 2 to 12 months (the extension is provided upon request) by attending courses and taking exams at the host university. At the end of the mobility period, the exams and the credits acquired are included in the student's regular university career at UniCal. The degree certificate released upon graduation documents international mobility by reporting exams and credits earned abroad.

2.2 Data description

The data used in the empirical analysis come from two main sources: administrative data on UniCal students and AlmaLaurea data on Italian graduates.

The first source of information regards participation in the Erasmus program and is provided by the International Office of UniCal for the 2005-2014 period. This dataset comprises information on all students applying for a mobility grant relating to the Erasmus program, the score and the position of students in the rankings for each year and each department.

As explained in the previous sub-section, each applicant included in the ranking is attributed a score that is determined in accordance with the selection rules in a specific year. Therefore, within each of these departmental rankings, we identify the cut-off point as the score of the last student who is offered an international mobility grant. The forcing variable *Ranking Score* for each student in the ranking is constructed as his/her score normalized to the cut-off score: it takes the value 0 for the last student and a positive (negative) value for those ranked higher (lower).

Table 1 reports the descriptive statistics of the main variables used in the empirical analysis.

The key variables we build for our analysis are: 1) *Assigned Erasmus*, a dummy variable that takes the value 1 if the student is assigned a grant for the Erasmus program, i.e. he/she records a score above or equal to 0, and 0 otherwise (in our sample roughly 44 percent of students are assigned an Erasmus grant); and 2) *Erasmus*, a dummy variable with the value 1 if the student accepts the grant and effectively participates in the mobility program and 0 otherwise (25.8 percent of applying students).

We match information on all students applying for Erasmus (treated and untreated) with our second source of data, i.e. AlmaLaurea, which provides details on both the academic careers and employment status of Italian graduates. We end up with a sample of 3,835 graduates who applied for the Erasmus program over the 2005-2014 period.

AlmaLaurea provides information on a number of graduate individual and academic characteristics, with details on family characteristics, types of degree, academic achievements, time taken to complete the degree, scholarships obtained and so on. Furthermore, the employment data are collected by AlmaLaurea through interviews one, three and five years after graduation, and disclose information on, among other things, type of employment, country of employment and other details relating to graduates' labor market outcomes.

We exploit information on the employment status of students interviewed three years after graduation[5] from UniCal to build our labor market outcomes and create the following variables: *Employed*, which takes the value 1 if graduates have a job at the time of the interview and 0 otherwise (with a mean of 0.497 in the sample), *Time to find a job,* which is measured as the months necessary to find a job after graduation (graduates in our sample take about 5.8 months on average to get a job after graduation), and *Job in line with studies*, which takes the value 1 if graduates have a job that is fully or partially consistent with their study path and 0 otherwise (50.1 percent of graduates in the labor market have a job in line with their studies).

For our empirical analysis we use also some educational outcomes. *Graduation grade* (with a mean of 103 and a St. Dev. of 7.73), *Distinction*, which takes the value 1 if the final grade is obtained with honors and 0 otherwise[6] (roughly 24 percent of students graduate with honors) and *Additional years to graduate*, measured as additional years beyond the official duration of the course needed to graduate (with a mean of 0.87 in the sample).[7]

[5]When we take information from interviews given five years after graduation, we observe many missing values in the outcome variables. Moreover, only a very small proportion of the graduates in our sample had already entered the job market one year after graduation.

[6]*Graduation grade* is expressed on a scale of 66-110, the minimum grade is 66/110 and the maximum grade is 110/110. "Honors" can be added to the maximum grade (110 cum laude).

[7]Typically, university students in Italy take much more time than expected to complete their academic career.

Personal data on graduates' profiles also allow us to get information on graduates and their families' characteristics. In particular, we build *Female*, which takes the value 1 for female graduates and 0 otherwise (51.8 percent of graduates in our sample are females), *Lyceum*, with the value 1 if students have attended a lyceum and 0 if the high-school attended was a technical/vocational school (23.2 percent of graduates in the sample come from a lyceum), and *Age* measuring the age of students at the time of enrolment (with a mean of 20.87 and a St. Dev. of 2.36). We also build the dummy variable *Province of residence*, which takes the value 1 if graduates come from the province where the university is located (Cosenza) and 0 otherwise. As regards the educational attainment of parents, we build a dummy with the value of 1 if at least one parent has a degree and 0 if they have a lower qualification (29.3 percent of graduates in our sample have at least one parent with a degree). Finally, we observe the field of study of graduates; in our sample most of them study Engineering (35.3 percent), Economics (21.2 percent), and Humanities (18.2 percent).

3 Econometric model and validity checks

3.1 Empirical strategy

In order to analyze the impact that the Erasmus program has on graduates' labor market outcomes, we adopt a Fuzzy Regression Discontinuity Design, taking into account the fact that the effective participation of students in the Erasmus program is not randomly assigned. In particular, a major concern in estimating the causal effect of interest is that students might have observable and unobservable characteristics which might affect both the decision to participate in the Erasmus program and their labor market outcomes, leading in turn to biased and inconsistent estimates.

In our setup, we are able to exploit the mechanism undertaken by UniCal—as explained in the previous section—in allocating mobility grants to students and so solve the aforementioned selection issue through a Fuzzy RDD. Our empirical strategy relies on a treatment status that is probabilistically determined as a discontinuous function of students' grant ranking score.

We have to take into account the fact that participation in the Erasmus program is not a deterministic function of the initial assignment since, on the one hand, some students above the threshold score might end up not accepting the mobility grant while, on the other hand, some students who are not offered admission to the program at first (below the cut-off) are

Garibaldi et al. (2012) report that the mean effective duration of a university program for a sample of graduates is 7.41, whereas the official duration is 4.39 years. About 41% of students were enrolled for more than the official length of their university program (so called "Fuori Corso").

subsequently admitted to participate in the mobility program—when winners do not accept the mobility grant—because they are in a position immediately below the cut-off in the ranking.

In order to deal with the endogeneity issues arising from the partial compliance of students to the Erasmus mobility program, we use the exogenous assignment to the treatment as an instrument for effective participation and apply an instrumental variable estimation approach. The Two-Stage-Least-Squares model we estimate is the following:

$$Y_{ikt} = \beta_0 + \beta_1 Erasmus_{ikt} + \beta_2 f(Ranking\ Score_{ikt}) + \beta_3 X_{ikt} + \mu_{kt} + \lambda_t + \tau_g + \varepsilon_{ikt} \tag{1}$$

$$Erasmus_{ikt} = \gamma_0 + \gamma_1 Assigned\ Erasmus_{ikt} + \gamma_2 g(Ranking\ Score_{ikt}) + \gamma_3 X_{ikt} + \mu_{kt} + \lambda_t + \tau_g + v_{ikt} \tag{2}$$

where Y_{ikt} is measured by some labor market outcomes (the probability of finding a job, the length of time necessary to find a job and the probability that the job is in line with the degree, respectively) of student i who is part of the departmental ranking k in the year t.

As explained above, the variable $Erasmus_{ikt}$ is a dummy with the value 1 if student i in departmental ranking k in year t studies abroad through the Erasmus mobility grant and 0 otherwise; $f(.)$ and $g(.)$ are polynomial functional forms that relate the forcing variable $Ranking\ Score_{ikt}$, built as the student normalized score during the year of application, to both labor market variables and the effective participation in the Erasmus mobility program.

Vector X_{ikt} includes a set of individual characteristics of student i, i.e. gender, high-school grade, type of high-school, age at the time of enrollment at university, a dummy taking the value of 1 if at least one of the parents has a degree and 0 if both parents have a lower educational attainment, and a dummy that takes the value of 1 if student i comes from the province where the university is located and 0 otherwise. Furthermore, to increase the precision of our estimates, we also add year of Erasmus application dummies λ_t, which take into account potential shocks affecting students—regardless of the ranking they belong to—specific to the year of application, year of graduation dummies τ_g and departmental ranking fixed effects μ_{kt}.[8] Finally, ε_{ikt} and ${}_{ikt}$ are the stochastic error terms of the model.

Equation (2) represents our First stage. The $Erasmus_{ikt}$ variable is instrumented with $Assigned\ Erasmus_{ikt}$. We estimate our model by using linear and quadratic polynomials of the running variable for the full sample (parametric approach) and a Local Linear Regression

[8] As suggested by Fort et al. (2022), exploiting the "within" variability around the cut-off is the most efficient way to guarantee identification of a meaningful causal effect in our setting for different reasons. First, the Erasmus mobility program is provided every year by different departments (Fuzzy RDD with multiple cut-offs); second, the treatment is allocated starting from the student with the highest score until exhaustion; last but not least, marginally exposed students are located exactly at the cut-off.

(LLR) approach in the neighborhood of the MSE-optimal bandwidth around the cut-off, as proposed by Calonico, Cattaneo and Farrell (2020). We also estimate separate functions on both sides of the cut-off point, by controlling for interaction terms between the polynomials of the forcing variable and $Erasmus_{ikt}$, and use the interaction terms between $g(Ranking\ Score_{ikt})$ and $Assigned\ Erasmus_{ikt}$ as instrumental variables.

Under the assumption that the relationship between the labor market variables and the ranking score is continuous near the threshold, the treatment assignment can be rated as good as random (Lee and Lemieux, 2010) and any jump in Y_{ikt} represents a treatment effect: the parameter β_1 represents the causal effect of the Erasmus program on labor market outcomes for compliers (*Local Average Treatment Effect* or *LATE*).

3.2 RDD validity tests

Before revealing the main results, we check whether the assumptions of the RDD are satisfied. We first present the McCrary test for the continuity of the forcing variable ($Ranking\ Score_{ik}$) by running a kernel local linear regression of the log of the density separately on both sides of the threshold (McCrary, 2008). If there is a discontinuity in the forcing variable at the cut-off point, students might, in principle, have manipulated the ranking score and sort below/above the threshold for inclusion in/exclusion from the Erasmus program. However, in our setting each ranking has its own threshold and the running variable is built as the normalized difference between the score of each student and that of the last applicant to whom a mobility grant is offered. As pointed out by Fort et al. (2022), a discontinuity in the density function of the running variable is unavoidable, given the large number of values equal to zero exactly at the cut-off, leading in turn to the failure of the manipulation test as proposed by McCrary (2008).

Following Fort et al. (2022), we include departmental ranking fixed effects that are specific for each year in our analysis in order to address the issue: in Figure 1, we present the density of the residuals of the ranking score after the inclusion of ranking fixed effects, showing no discontinuity in the neighborhood of the threshold (the difference is 0.022; Standard Error: 0.114). These results reassure us that students do not have any great control over the forcing variable. This is also expected as the ranking for inclusion in the mobility program is independently determined by each department and the cut-off is determined ex-post on the basis of the number and characteristics of students applying for an Erasmus mobility grant each year.

As in any standard RD design, we evaluate the continuity at the cut-off point in the distribution of the covariates included in our regressions. The idea is to regress each covariate on a first- or second-order polynomial of the forcing variable along with a dummy for the treatment status: a statistically insignificant coefficient for the treatment dummy is taken as evidence in favor of local random assignment (see, among others, Caughey and Sekhon, 2011; Lee, 2008). In specifications (1) and (2) of Table 2, in which we use the full sample, we control for a linear and quadratic polynomial of the forcing variable along with a first- and second-order interaction term between the assignment variable and the treatment status, and for ranking dummies, respectively. The results reveal that only one covariate (*High-school grade*) out of a broad set is discontinuous around the cut-off (see column 2). Moreover, when in the last specification we use a LLR within the MSE-optimal bandwidth (selected for each covariate) in the neighborhood of the threshold we find strong evidence that the treatment is not predictive of the control variables, which reassures us about the randomness of the assigned treatment around the cut-off.

As a final check, we present some descriptive graphs of the predetermined characteristics plotted against the ranking score near the threshold in Figure 2. Each panel shows the assignment variable cell means of the predetermined characteristics in the proximity of the ranking score threshold along with the fitted values of a locally weighted second order regression that is calculated within each segment. Overall, Figure 2 confirms that covariates do not exhibit any significant jump around the cut-off.

4 Main results

In this section, we report 2SLS estimates of the effect that participation in the Erasmus mobility program produces on graduates' labor market outcomes, where effective participation in the Erasmus program is instrumented by the initially assigned treatment.

Table 3 displays our findings when the outcome variable is *Employment*, i.e. the probability of finding a job. We adopt a parametric Fuzzy RDD on the full sample and add a first-order polynomial of the forcing variable along with a linear interaction term between the treatment status and the assignment variable among regressors from column (1) to (3). Instead, in the last specification we control for a quadratic polynomial of the forcing variable and for a second-order interaction term between $Erasmus_{ikt}$ and $Ranking\ Score_{ikt}$. In each specification, standard errors are robust to heteroskedasticity and clustered at the departmental ranking level.

In Panel (b) of Table 3, we report the First-stage estimates. The assigned treatment strongly correlates with the effective treatment, since being assigned to the treatment around the threshold leads to an increase in the probability of studying abroad through the Erasmus program of about 50–53 percentage points. These findings are also confirmed by Figure 3, which shows a large discontinuity in the probability of participating in the international mobility program: for those who scored above the threshold in the ranking this probability is 0.53, while it drops to just 0.015 for students who obtained a score below the cut-off.

2SLS estimates—Panel (a) of Table 3—show a positive and statistically significant effect of our variable of interest on the probability of being employed. In particular, in column (3)—where we add the full set of covariates—our findings highlight an increase in the probability of finding a job of 16.1 percentage points. Once we control for departmental ranking dummies (from column 2), adding individual covariates does not change our estimates since the coefficient of $Erasmus_{ikt}$ is stable across specifications both in terms of significance and magnitude. The results are also similar to those reported in column (3) when, instead, we use a second-order polynomial of the assignment variable (see column 4): again, participation in the program leads to an upward shift in the probability of finding employment of 10 percentage points and the effect is significant at the 10 percent level.

Among the control variables, we find that students with a higher final mark obtained in their high-school diploma show a higher probability of being employed, whereas younger students and those from more educated families seem to be penalized in terms of finding a job.[9] Instead, no correlation emerges between our outcome and the gender of students and the type of high-school attended.

In Table 4, we focus on the sub-sample of employed graduates and show the effect that participation in the Erasmus program generates on further labor market outcomes, i.e. the time (expressed in months) necessary to find a job after graduation, and the probability of having a job in line with the awarded degree. In all specifications we add the full set of controls, whereas in odd (even) columns we control for a linear (quadratic) polynomial of the forcing variable and for a first-order (second-order) interaction term between the effective treatment dummy and the assignment variable.

In column (1), our findings highlight that actively participating in the international mobility program leads to a decrease in the time (expressed in months) spent by students to find a job after graduation of 2.14 months. Nothing relevant changes when we control for a second-order polynomial of the forcing variable in column (2): the coefficient of the effective treatment is

[9] It might be that these graduates spend more time to find a good job.

still negative and statistically significant at the 1 percent level, although a bit larger in terms of magnitude than the point estimate reported in the previous specification.

On the other hand, in column (3) and (4) we use the probability of finding a job in line with the field of study as a dependent variable: we do not find any evidence that participation in the Erasmus program affects this outcome variable.[10]

Our estimation results reported in Table 3 and 4 are also consistent with the descriptive graphs presented in Figure 4, in which we plot all the labor market outcomes against the normalized ranking score close to the cut-off. In each panel, the blue central line is a second-order polynomial fit, whereas the green lateral lines are the confidence intervals at the 95 percent level. Furthermore, scatter points represent the average of the outcome within each of the 100 bins built. Overall, Figure 4 highlights a discontinuity in the probability of being employed and in the months spent to find a job at the cut-off of zero, whereas no jump is detected in the probability of finding a job in line with study activities.

In Table 5, we present non-parametric Fuzzy RDD estimates by using a Local Linear Regression (LLR) approach in the neighborhood of the MSE-optimal bandwidth around the threshold of zero in the ranking score (Calonico, Cattaneo and Farrell, 2020). We always control for the full set of covariates and add a first-order interaction term between the treatment status and the forcing variable. All in all, the effect that participation in the Erasmus program produces on the labor market outcomes is similar in terms of magnitude to that shown in Table 3 and 4, in which we used a parametric Fuzzy RDD for the full sample.[11]

[10] Although the total number of employed graduates in our sample is 1,832, only 1,091 respondents answer questions in AlmaLaurea survey asking information on the time necessary to find a job after graduation and only 1,101 graduates indicate whether the job is in line with the acquired degree. A potential concern of our analysis is that actively participating in the Erasmus mobility program may affect graduates' response rates to the above questions. Therefore, we build dummy variables which take the value 1 for missing values in both labor market outcomes and 0 otherwise. The results, available upon request, show no significant discontinuity in these variables near the cut-off.

[11] Almalaurea provides information on further labour market variables, such as the type of contract (full-time/part-time and permanent/fixed-term) and the level of satisfaction with the job (measured on a scale ranging from a minimum of 1—*not at all*—to a maximum of 10—*very much*). Accordingly, we build the dummy variables *Full* and *Permanent* that take, respectively, 1 if the respondent has a full-time or a permanent job and 0 otherwise, and the variable *High satisfaction* that is equal to 1 if the level of job satisfaction is above the median value of 7 and 0 otherwise. However, we do not find any significant effect of participating in the Erasmus program on these three outcomes, no matter the empirical specification used. We also focus on a question in the Almalaurea survey asking respondents about the monthly remuneration, split into 14 classes with a width of 250 euros each (the first remuneration class is *below 250 euros*, whereas the last one is *above 3,000 euros*). Again, we build a dummy variable *High remuneration* taking 1 for values above the median of 5 and 0 otherwise, and find that our variable of interest leads to an increase in the probability of having a higher remuneration (above 1,000 euros) of 19.2 percentage points (p-value: 0.085) in the neighbourhood of the MSE-optimal bandwidth. Nevertheless, the effect is not stable across specifications in terms of significance and magnitude. We have also built the variable *Remuneration* imputing for each employed the average value within the corresponding remuneration class, and our estimates reveal that participating in the Erasmus program increases the average wage by about 177 euros within the MSE-optimal bandwidth, although the p-value rises up to 0.187 (the findings are available upon request). Notice that the estimates reported in this footnote are based only on the sub-sample of employed graduates.

These results are also robust across a wide range of bandwidths, regardless of the optimization procedure adopted. Following Grembi, Nannicini and Troiano (2016), in Figure 5 we plot Fuzzy RDD estimates on our labor market outcomes along with the 90 percent confidence intervals, choosing different bandwidths from 0.5 to 15 (every 0.1 points) around the forcing variable $Ranking\ Score_{ik}$. The vertical dotted line refers to the MSE-optimal bandwidth used in the main specifications reported in Table 5. Figure 5 shows that the coefficients are not sensitive to the chosen bandwidth and are stable near the MSE-optimal bandwidth.

We also analyze whether participation in the Erasmus program generates heterogeneous effects on our labor market outcomes across different dimensions, i.e. gender, type of degree and field of study.

As regards the gender of graduates, the results reported in Table 6 highlight how studying abroad through the Erasmus program only produces a positive impact on the probability of finding a job in the sub-sample of male students, i.e. participation in the program leads to an upward shift in the outcome variable of about 23.6 percentage points. Similar results are found when we control for a second-order polynomial of the forcing variable (column 3 and 4) and when we adopt a LLR within the MSE-optimal bandwidth around the cut-off (column 5 and 6). Instead, no differential effect by gender of graduates who applied for the international mobility program is detected on both the time necessary to find a job and the probability of getting a job in line with their study path (see Table A1 in the Appendix of the paper).

Moreover, in Table 7 we report estimates separately for students attending a Bachelor or a Master's degree course.[12] As expected, the findings show that the positive effect on the probability of employment is significant and large in magnitude for Master's graduates. In particular, participation in the Erasmus program causes an increase in the likelihood of finding a job ranging between 13 and 21 percentage points for Master's graduates. The results displayed in Table A2 also show that undergraduates studying abroad through the international mobility program take less time than Master's graduates to find a job after graduation.

Finally, we evaluate whether studying abroad through the Erasmus program produces differentiated effects on the probability of employment for STEM (Science, Technology, Engineering and Mathematics) students—accounting for 42.5 percent of graduates in our sample—compared with those enrolled on other degree courses. We run Fuzzy RDD estimations by splitting the sample according to students' field of study and display the results in Table

[12] In our sample 43.2 percent of students attended a Bachelor degree course.

8. We find a positive and statistically significant impact of our variable of interest only on the probability of getting a job in the sub-group of STEM graduates, regardless of the estimation procedure adopted. In particular, studying abroad with Erasmus leads to an upward shift in our outcome variable of 22-24 percentage points for STEM students, whereas a lower effect is detected for non-STEM students (see column 5 and 6): the difference in the point estimates between the two groups of graduates is also statistically significant at conventional levels. A differential effect on both the probability of finding a job in line with the awarded degree and the time necessary to find a job also emerges for STEM graduates (see Table A3).

5 Intention-To-Treat analysis

Given that policymakers might be interested in understanding the expected benefits of the Erasmus mobility program for target students, we also focus on Intention-To-Treat (ITT) effects (Heckman et al., 1999). In order to recover ITT estimates, we use a Sharp Regression Discontinuity Design (Sharp RDD hereafter) in which the treatment status is simply defined by the assignment rule (Imbens and Lemieux, 2008; Angrist and Pischke, 2009), which corresponds to the reduced form of our model (Equation 1 and 2):

$$Y_{ikt} = \alpha_0 + \alpha_1 Assigned\ Erasmus_{ikt} + \alpha_2 h(Ranking\ Score_{ikt}) + \alpha_3 X_{ikt} + \mu_{kt} + \lambda_t + \tau_g + v_{ikt} \quad (3)$$

The results are reported in Table 9. In columns (1)-(3), the outcome variable is the probability of being employed. In particular, when we adopt a LLR within the MSE-optimal bandwidth near the threshold and control for a linear polynomial of the assignment variable along with a first-order interaction term between the treatment and the forcing variable, we find that $Assigned\ Erasmus_{ikt}$ leads to an increase in the probability of finding a job of 7.2 percentage points and the effect is significant at the 10 percent level (see column 3).

In columns (4)-(6) and (7)-(9), instead, we focus respectively on the time necessary to find a job after graduation and on the probability of getting a job in line with the field of study. Again, we find that assignment to treatment negatively affects the former, whereas no effect is found on the latter, regardless of the estimation procedure adopted.

All in all, we find that ITT estimates are in line with 2SLS estimates previously reported in Table 4 and 5, and, as expected, smaller in terms of magnitude. Finally, by replicating the analysis of Figure 5, we also show that ITT estimates do not vary according to the selected window near the MSE-optimal bandwidth in Figure 6.

6 Mechanisms

The key finding of our analysis is that participating in the Erasmus program improves employment probability and that the effect is driven by males and STEM graduates. In this sub-section, we discuss candidate explanations of these results by implementing a LLR within the MSE-optimal bandwidth in the neighborhood of the cut-off.

First, we focus on the impact that participation in the program produces on academic outcomes, which in turn might affect occupational prospects. It is well recognized that international education plays a role as a skill builder, since students usually benefit from exposure to a different cultural context and learn a new language.

In order to understand whether Erasmus experience improves students' foreign language skills, which is the most immediate benefit deriving from this type of experience, we focus on proficiency in the English language, which is nowadays considered as a key component of professional success. With this aim, we exploit a section in the AlmaLaurea survey which includes questions about the level of proficiency of graduates in both written and oral English language. The possible answers to these questions are "none", "basic knowledge" and "good knowledge". Accordingly, we build two dummy variables, i.e. *Written English* and *Oral English*, taking the value of 1 for graduates who answered "good knowledge" and 0 otherwise. The results, reported in column (1) and (2) of Table 10, show that Erasmus mobility only affects the level of proficiency in spoken English: the coefficient of the treatment variable is positive and significant at the 10 percent level.

Moreover, given that international education might also signal some important personal traits that graduates have, such as openness, adaptation ability and mobility propensity, we exploit two questions in the AlmaLaurea survey which ask graduates about their availability to work outside Italy, either in a European country or in a country outside Europe. In this case, the potential answers to these questions are "no", "more likely no than yes", "more likely yes than no" and "yes". We build two additional dummies, *Work in Europe* and *Work outside Europe*, with the value 1 if students answered either "more likely yes than no" or "yes" and 0 otherwise and use them as outcomes in our empirical analysis. The results are displayed in columns (3) and (4) of Table 10 and show that studying abroad positively affects the propensity to work abroad in a European country by 38.1 percentage points. No effect is detected on the probability of working outside Europe, and this might be due to the fact that none of graduates in our sample studied in an

Extra-EU country.[13][14]

Second, we investigate whether the program reflects better academic outcomes by analyzing its impact on the final graduation mark, the possibility of graduating with honors and time taken to graduate. As shown in Table 11, spending a period of time studying abroad positively affects both the graduation mark (+2.48 p.p., p-value: 0.000) and the probability of graduating with honors (+12.2 p.p., p-value: 0.127), while no effect is found on the additional years needed for graduation. We also show that the effect on the graduation mark and on the probability of getting the honors is larger for male than for female students and for STEM graduates (see Table A4 and A5).

These results are similar to those found by Granato et al. (2022) for students enrolled at the University of Bologna (Italy). They also show that the benefits are limited to students' performances while abroad, which might depend on lower grading standards adopted towards Erasmus students or driven by students hosted in institutions of relatively lower quality. Our data does not allow investigation of whether the positive effect we found derives from the performance at exams taken during the period abroad. However, we look at whether the effect is heterogeneous according to the quality of the host university. With this aim, we use the Shanghai Academic Ranking of World Universities, which ranks about 2,000 universities every year on the basis of a number of research and academic quality indicators,[15] and we run separate regressions, firstly including only students hosted in institutions with a score in the ranking below 100 (high-quality universities) and, then, those above the score of 100 (lower quality universities).[16] As shown in Table 12, the positive effect on the final graduation mark is detected for both samples, but is higher in terms of magnitude for students who spend a period of study in an institution of relatively higher quality.

Similar results to those displayed in Table 12 are also found when we measure our outcome variable in terms of probability of getting a job (see Table A6), whereas no differential effect based on the quality of host institutions is shown on the time necessary to find a job after graduation and on the probability of finding an employment in line with the study path.

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[13] We have also analyzed the effect of participating in the Erasmus program on the probability of working abroad: we find a positive, but not significant coefficient. This is probably due to the fact that working abroad is rare in our sample (only 84 students).

[14] It should be noticed that questions about language proficiency and preferences for future careers are asked in the Almalaurea questionnaire at graduation, whereas questions on labor market characteristics are asked three years after graduation.

[15] The yearly Shanghai rankings are available on line at the following address http://www.shanghairanking.com.

[16] The same group of students is used as a control in both sub-samples. Obviously, this occurs because we do not have information about the host university for Non-Erasmus students.

We finally investigate whether the length of time spent abroad might explain the effect observed on the educational and labor market outcomes. In particular, we distinguish between students who spent longer or shorter periods of study abroad (below/above the median value of 5 months) and run separate regressions for each group. The results reported in Table 13 show a positive effect of the Erasmus mobility program on the graduation mark in both sub-samples, but again the impact is stronger in magnitude for graduates who spent a longer period of study abroad. This differential effect on the graduation mark also translates into a positive impact on labor market outcomes, i.e. we find a greater impact in terms of magnitude (statistically significant at the 10 percent level) on the probability of finding a job for graduates who studied abroad for more than 5 months (see Table A7).

7 Concluding remarks

In European countries, the Erasmus project is a fundamental program for encouraging student mobility, promoting social integration and common European values, improving students' language skills, and helping them acquire a number of cognitive and non-cognitive skills.

However, there is no sufficient rigorous evidence of its causal impact on students' labor market outcomes. In this paper, we shed light on this aspect by using a large sample of students from the University of Calabria who applied to participate in the Erasmus program. We match administrative data from university records with the AlmaLaurea survey, which provides information on labor market outcomes three years after graduation.

We exploit the fact that, due to the large number of applications, students in each department and each year are assigned a mobility grant for the Erasmus program on the basis of a score determined by the number of credits acquired and by the average grade at passed exams.

In order to identify the impact of interest, we implement a Regression Discontinuity Design, basically comparing the labor market outcomes of students just above the threshold for the awarding of an Erasmus grant with students just below this threshold. Since a number of students do not comply with the initial assignment of grants (some students give up to participate and others are called to replace them), we use a Fuzzy Design to take into account the partial compliance.

Our estimates show that participating in the Erasmus program significantly increases, for the graduates in our sample, the probability of being employed three years after graduation and reduces the time necessary to find a job. The positive effects are mainly driven by male and

STEM graduates.

When we investigate the mechanisms, we find that the Erasmus experience positively affects the graduation mark, especially for students hosted in highly-ranked universities, and the probability of graduating with honors. Also, the period spent abroad seems to improve students' proficiency in spoken English. Furthermore, participation in the Erasmus program tends to increase the propensity of graduates to move in order to find a job.

Unfortunately, our data do not allow us to gather information on non-cognitive skills. Future research should analyze this aspect since participation in the international mobility program might also affect individuals' soft skills, such as openness to new experience, independence or flexibility.

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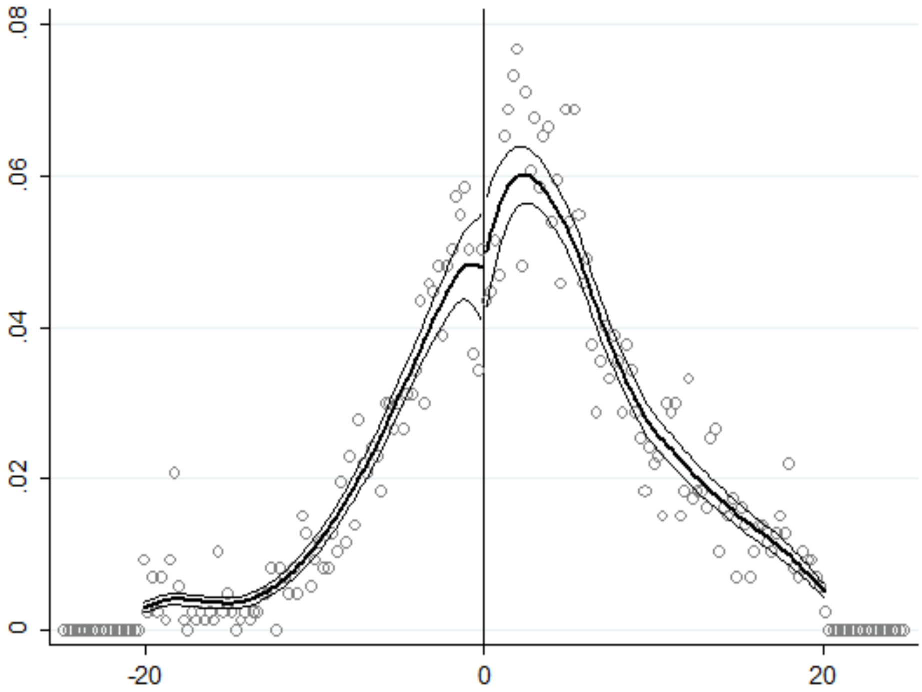
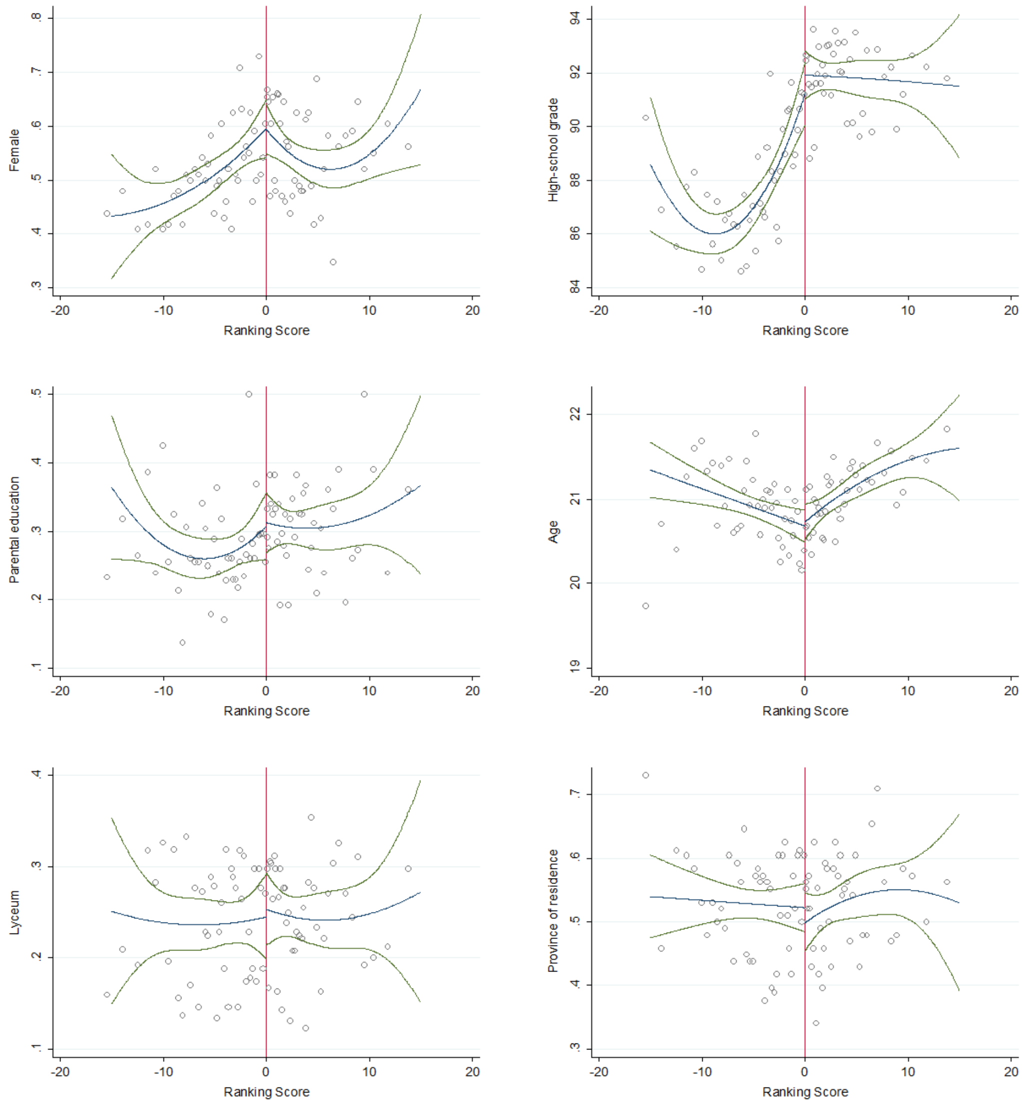
List of figures and tables

Figure 1: Manipulation of the forcing variable at the cut-off



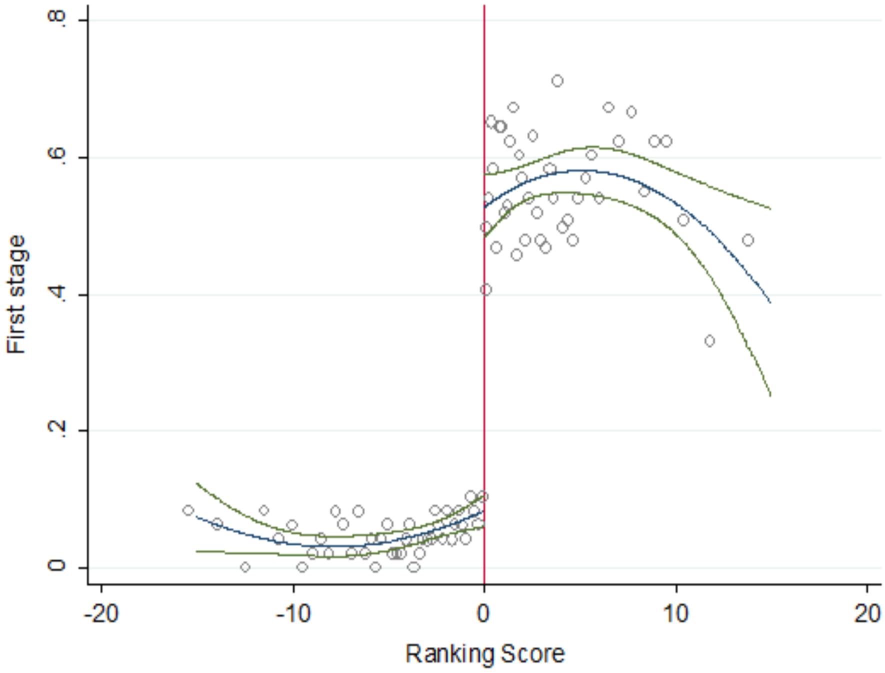
Notes. We present a weighted kernel estimation of the log density (forcing variable: *Ranking Score*) performed separately on either side of the cut-off. Optimal bandwidth and bin size as in McCrary (2008). The McCrary test is performed on the density of the running variable once ranking fixed effects are taken into account.

Figure 2: Discontinuity in the covariates at the cut-off



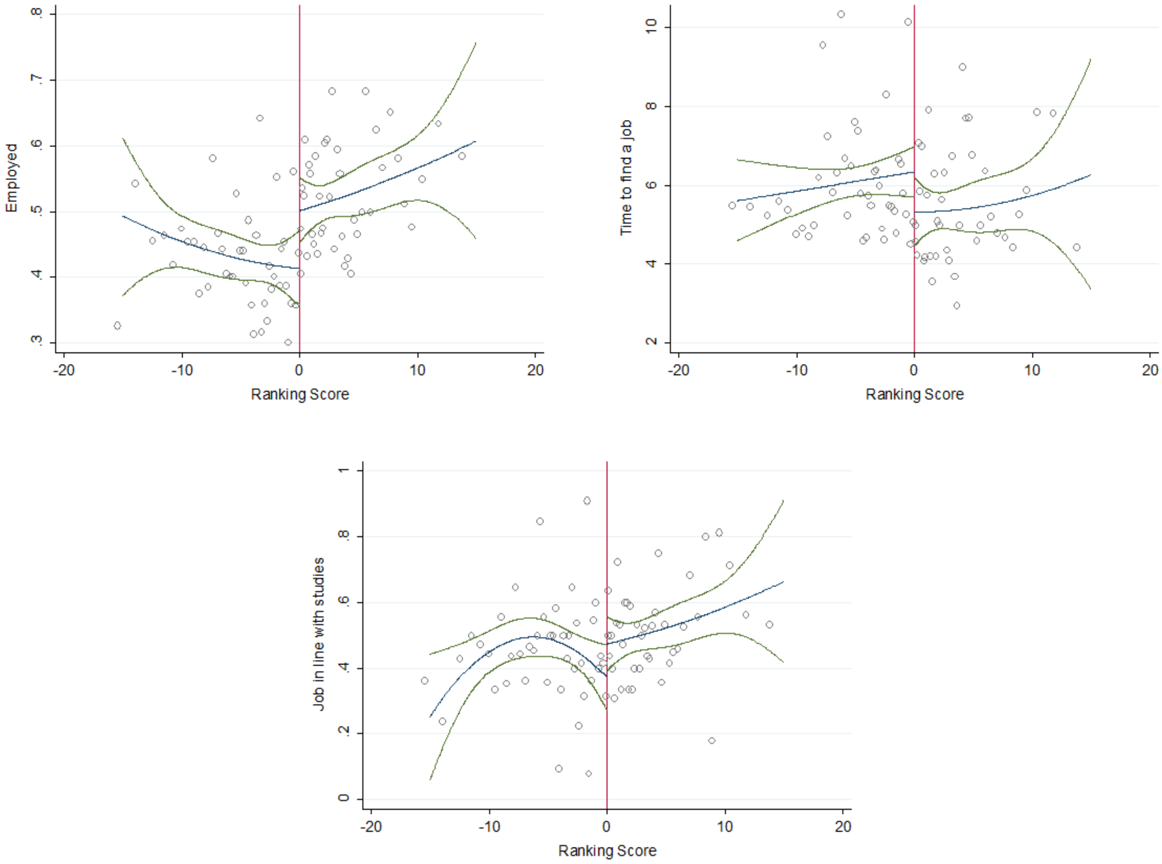
Notes. We report the discontinuity in the covariates added to the econometric model. The solid line is a running-mean smoothing (second order) of the variable on the vertical axis, performed separately on either side of the cut-off. The dots are the observed values averaged within each of the 100 bins built. We also report confidence intervals at the 95 percent level.

Figure 3: Discontinuity in the probability of participating in the Erasmus program



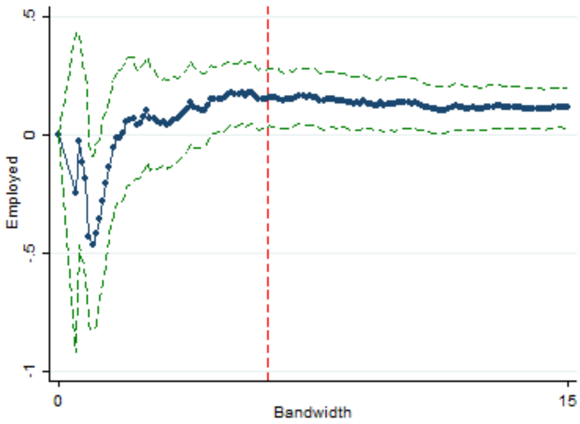
Notes. We report the discontinuity in the probability of participating in the Erasmus program. The solid line is a running-mean smoothing (second order) of the variable on the vertical axis, performed separately on either side of the cut-off. The dots are the observed values averaged within each of the 100 bins built. We also report confidence intervals at the 95 percent level.

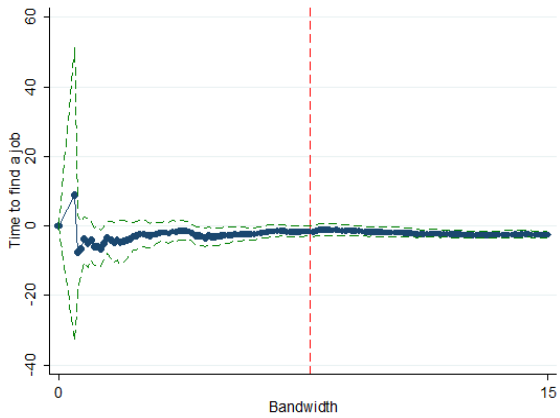
Figure 4: Discontinuity in the labour market outcomes at the cut-off

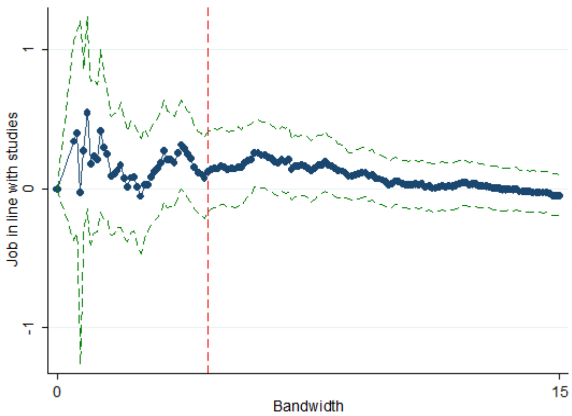


Notes. We report the discontinuity in the labour market outcomes. The solid line is a running-mean smoothing (second order) of the variable on the vertical axis, performed separately on either side of the cut-off. The dots are the observed values averaged within each of the 100 bins built. We also report confidence intervals at the 95 percent level.

Figure 5: Sensitivity to different bandwidths – Fuzzy RDD

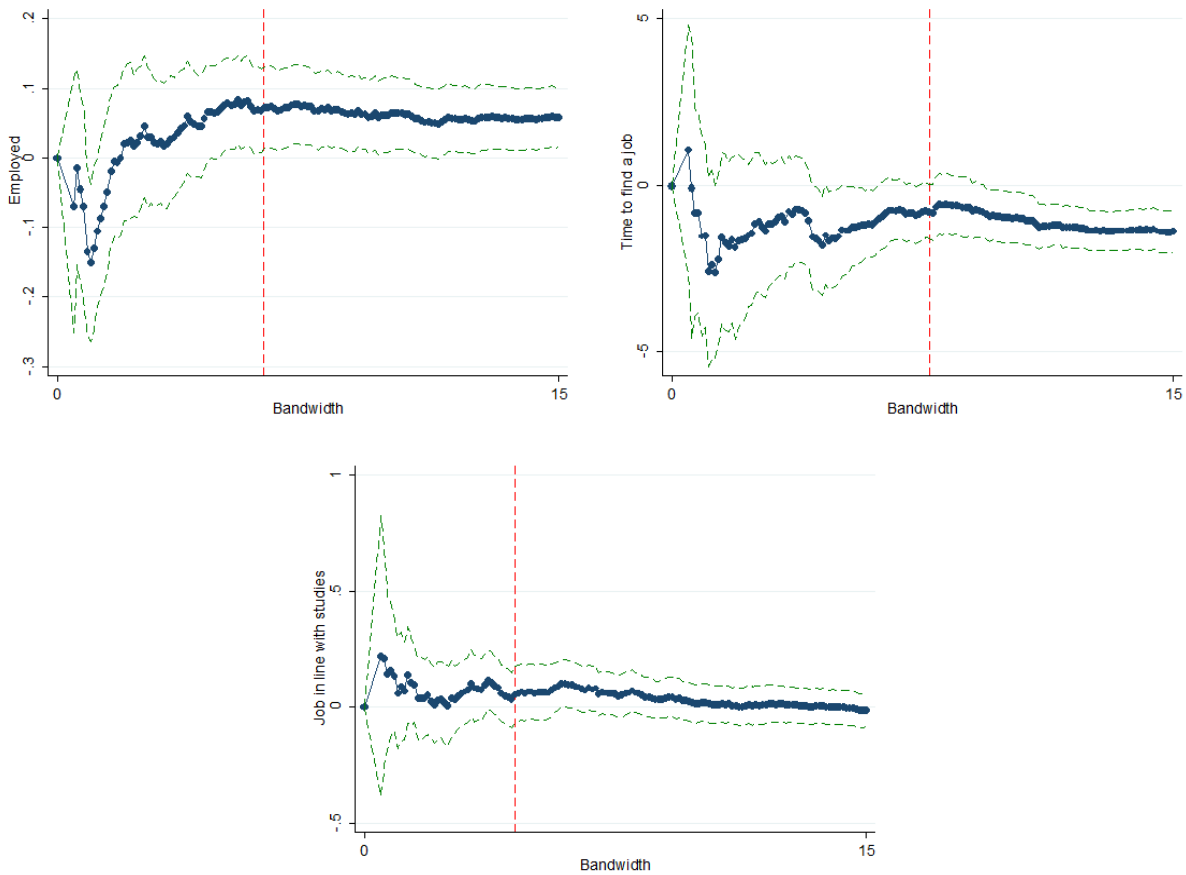






Notes. Fuzzy RDD estimates. Vertical axis: Fuzzy RDD coefficients. Horizontal axis: bandwidth used to estimate the reported Fuzzy RDD coefficients. We also report confidence intervals at the 90 percent level.

Figure 6: Sensitivity to different bandwidths – Sharp RDD



Notes. Sharp RDD estimates. Vertical axis: Sharp RDD coefficients. Horizontal axis: bandwidth used to estimate the reported Sharp RDD coefficients. We also report confidence intervals at the 90 percent level.

Table 1: Descriptive statistics

Variables	Obs	Mean	St. dev.	Min	Max
Outcomes					
Employed	3,835	0.478	0.499	0	1
Time to find a job	1,091	5.826	4.57	1	36
Job in line with studies	1,101	0.501	0.5	0	1
Graduation grade	3,835	103.193	7.795	74	111
Distinction	3,835	0.244	0.429	0	1
Additional years to graduate	3,834	0.879	1.219	0	8.394
Erasmus	3,835	0.258	0.438	0	1
Assigned Erasmus	3,835	0.441	0.496	0	1
Ranking Score	3,835	-4.777	14.152	-50.615	23.666
Controls					
Female	3,835	0.518	0.5	0	1
High-school grade	3,835	89.44	10.703	60	100
Age	3,835	20.879	2.358	18	41
Lyceum	3,835	0.232	0.422	0	1
Province of residence	3,835	0.535	0.499	0	1
Parental education	3,835	0.293	0.455	0	1
Field of study: Economics	3,835	0.212	0.409	0	1
Field of study: Pharmacy	3,835	0.074	0.262	0	1
Field of study: Engineering	3,835	0.353	0.478	0	1
Field of study: Humanities	3,835	0.182	0.386	0	1
Field of study: Maths and Science	3,835	0.072	0.259	0	1
Field of study: Political Science	3,835	0.107	0.309	0	1

Source: Administrative data provided by the University of Calabria matched with AlmaLaurea (2005-2014).

Table 2: Balance test on covariates

	First-order polynomial	**Second-order polynomial**	**MSE-optimal bandwidth**
Female	0.014	0.024	-0.013
	(0.019)	(0.023)	(0.030)
High-school grade	2.863***	1.752***	0.867
	(0.522)	(0.531)	(0.753)
Parental education	0.035	-0.005	0.014
	(0.021)	(0.027)	(0.035)
Age	-0.080	-0.202	0.237
	(0.185)	(0.163)	(0.182)
Lyceum	0.004	0.006	0.008
	(0.017)	(0.023)	(0.036)
Province of residence	-0.024	-0.022	-0.052
	(0.022)	(0.029)	(0.034)

Notes. Baseline RDD estimates. In columns (1) and (2), we control for a linear and quadratic polynomial of the forcing variable using the full sample of students, respectively. In column (3), we focus on students within the MSE-optimal bandwidth for each covariate. We always control for departmental ranking dummies. Standard errors are robust to heteroskedasticity and clustered at the departmental ranking level (shown in brackets). Significance at the 10 percent level is represented by *, at the 5 percent level by **, and at the 1 percent level by ***.

Table 3: Erasmus program and the probability of being employed. Fuzzy RDD estimates

	(1)	(2)	(3)	(4)
	Panel (a): 2SLS			
Erasmus	0.205***	0.147***	0.161***	0.100*
	(0.065)	(0.055)	(0.046)	(0.060)
Female			-0.025	-0.027
			(0.020)	(0.020)
High-school grade			0.003***	0.003***
			(0.001)	(0.001)
Age			0.052***	0.052***
			(0.005)	(0.006)
Lyceum			-0.004	-0.002
			(0.018)	(0.018)
Province of residence			0.028*	0.028*
			(0.016)	(0.017)
Parental education			-0.049***	-0.052***
			(0.018)	(0.018)
	Panel (b): First stage			
Assigned Erasmus	0.513***	0.520***	0.527***	0.505***
	(0.026)	(0.025)	(0.026)	(0.029)
F-stat	217.21	211.37	212.66	135.61
p-value	0.000	0.000	0.000	0.000
Polynomial Forcing Variable	First	First	First	Second
Interaction term	Yes	Yes	Yes	Yes
Departmental ranking FE	No	Yes	Yes	Yes
Year of application FE	No	Yes	Yes	Yes
Year of graduation FE	No	Yes	Yes	Yes
Student characteristics	No	No	Yes	Yes
Parent characteristics	No	No	Yes	Yes
Observations	3,835	3,835	3,835	3,835
R-squared		0.147	0.202	0.204

Notes. Parametric Fuzzy RDD estimates. The outcome variable is the probability of finding a job. From column (1) to (3), we control for a first-order polynomial of the assignment variable and for a first-order interaction term between the treatment and the ranking score. In the last specification (column 4), we add a second-order polynomial of the assignment variable along with a second-order interaction term. Standard errors are robust to heteroskedasticity and clustered at the departmental ranking level (reported inside the brackets). Significance at the 10 percent level is represented by *, at the 5 percent level by **, and at the 1 percent level by ***.

Table 4: Erasmus program and further labour market outcomes. Fuzzy RDD estimates

	(1) Time to find a job	(2) Time to find a job	(3) Job in line with studies	(4) Job in line with studies
Panel (a): 2SLS				
Erasmus	-2.145***	-2.315***	-0.005	-0.131
	(0.601)	(0.716)	(0.087)	(0.121)
Female	-0.223	-0.250	-0.024	-0.023
	(0.329)	(0.340)	(0.040)	(0.042)
High-school grade	-0.013	-0.013	0.001	0.001
	(0.015)	(0.015)	(0.001)	(0.002)
Age	-0.108*	-0.101	0.021***	0.020**
	(0.063)	(0.069)	(0.008)	(0.008)
Lyceum	-0.178	-0.149	-0.046	-0.038
	(0.399)	(0.393)	(0.048)	(0.047)
Province of residence	-0.402	-0.397	0.009	0.002
	(0.287)	(0.290)	(0.030)	(0.031)
Parental education	0.190	0.174	0.119***	0.124***
	(0.274)	(0.278)	(0.037)	(0.035)
Panel (b): First stage				
Assigned Erasmus	0.562***	0.571***	0.544***	0.475***
	(0.042)	(0.050)	(0.043)	(0.060)
F-stat	100.02	56.21	86.75	48.88
p-value	0.000	0.000	0.000	0.000
Polynomial Forcing variable	First	Second	First	Second
Interaction term	Yes	Yes	Yes	Yes
Departmental ranking FE	Yes	Yes	Yes	Yes
Year of application FE	Yes	Yes	Yes	Yes
Year of graduation FE	Yes	Yes	Yes	Yes
Student characteristics	Yes	Yes	Yes	Yes
Parent characteristics	Yes	Yes	Yes	Yes
Observations	1,091	1,091	1,101	1,101
R-squared	0.193	0.192	0.108	0.105

Notes. Parametric Fuzzy RDD estimates. The outcome variable is reported at the top of each column. In odd columns, we control for a first-order polynomial of the assignment variable and for a first-order interaction term between the treatment and the ranking score. In even columns, we add a second-order polynomial of the assignment variable along with a second-order interaction term. Standard errors are robust to heteroskedasticity and clustered at the departmental ranking level (reported inside the brackets). Significance at the 10 percent level is represented by *, at the 5 percent level by **, and at the 1 percent level by ***.

Table 5: Erasmus program and labour market outcomes. Fuzzy RDD estimates. LLR with MSE-bandwidth

	(1) Employed	(2) Time to find a job	(3) Job in line with studies
Panel (a): 2SLS			
Erasmus	0.155**	-1.497*	0.117
	(0.077)	(0.946)	(0.178)
Female	0.002	0.014	0.021
	(0.024)	(0.336)	(0.051)
High-school grade	0.002*	-0.017	-0.001
	(0.001)	(0.018)	(0.003)
Age	0.062***	-0.168**	0.039***
	(0.007)	(0.080)	(0.012)
Lyceum	-0.015	-0.604	-0.004
	(0.020)	(0.436)	(0.069)
Province of residence	0.034	-0.106	0.043
	(0.022)	(0.344)	(0.053)
Parental education	-0.053**	0.365	0.080*
	(0.022)	(0.346)	(0.044)
Panel (b): First stage			
Assigned Erasmus	0.472***	0.500***	0.453***
	(0.030)	(0.055)	(0.084)
F-stat	130.74	45.69	18.09
p-value	0.000	0.000	0.000
Optimal bandwidth	MSE	MSE	MSE
Polynomial Forcing variable	First	First	First
Interaction term	Yes	Yes	Yes
Departmental ranking FE	Yes	Yes	Yes
Year of application FE	Yes	Yes	Yes
Year of graduation FE	Yes	Yes	Yes
Student characteristics	Yes	Yes	Yes
Parent characteristics	Yes	Yes	Yes
Observations	2,266	749	496
R-squared	0.241	0.252	0.210

Notes. Fuzzy RDD estimates within the MSE-optimal bandwidth. The outcome variable is reported at the top of each column. In every specification, we control for a first-order polynomial of the assignment variable and for a first-order interaction term between the treatment and the ranking score. Standard errors are robust to heteroskedasticity and clustered at the departmental ranking level (reported inside the brackets). Significance at the 10 percent level is represented by *, at the 5 percent level by **, and at the 1 percent level by ***.

Table 6: Erasmus program and the probability of employment by gender. Fuzzy RDD estimates.

	(1) Employed	(2) Employed	(3) Employed	(4) Employed	(5) Employed	(6) Employed
	Female	Male	Female	Male	Female	Male
			Panel (a): 2SLS			
Erasmus	0.073	0.236***	-0.008	0.217***	0.094	0.218**
	(0.062)	(0.065)	(0.083)	(0.075)	(0.100)	(0.110)
			Panel (b): First stage			
Assigned Erasmus	0.505***	0.547***	0.482***	0.527***	0.449***	0.494***
	(0.025)	(0.038)	(0.031)	(0.044)	(0.036)	(0.042)
F-stat	226.22	108.30	116.99	59.19	84.44	85.04
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Sample	Full	Full	Full	Full	MSE	MSE
Polynomial Forcing variable	First	First	Second	Second	First	First
Interaction term	Yes	Yes	Yes	Yes	Yes	Yes
Departmental ranking FE	Yes	Yes	Yes	Yes	Yes	Yes
Year of application FE	Yes	Yes	Yes	Yes	Yes	Yes
Year of graduation FE	Yes	Yes	Yes	Yes	Yes	Yes
Student characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Parent characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,985	1,850	1,985	1,850	1,232	1,034
R-squared	0.210	0.222	0.190	0.227	0.260	0.271

Notes. Fuzzy RDD estimates. The outcome variable is reported at the top of each column. In odd columns, we focus on the sample of female students and, in even columns, on the sample of male students. In specifications (1) and (2), we control for a first-order polynomial of the assignment variable and for a first-order interaction term between the treatment and the ranking score for the full sample. In specifications (3) and (4), we add a second-order polynomial of the assignment variable along with a second-order interaction term. In specifications (5) and (6), we implement a LLR within the MSE-optimal bandwidth. Standard errors are robust to heteroskedasticity and clustered at the departmental ranking level (reported inside the brackets). Significance at the 10 percent level is represented by *, at the 5 percent level by **, and at the 1 percent level by ***.

Table 7: Erasmus program and the probability of employment by Bachelor/Master graduates. Fuzzy RDD estimates.

	(1) Employed	(2) Employed	(3) Employed	(4) Employed	(5) Employed	(6) Employed
	Bachelor	Master	Bachelor	Master	Bachelor	Master
			Panel (a): 2SLS			
Erasmus	0.031	0.153***	-0.157	0.130*	-0.040	0.206*
	(0.058)	(0.055)	(0.103)	(0.066)	(0.090)	(0.109)
			Panel (b): First stage			
Assigned Erasmus	0.496***	0.561***	0.445***	0.539***	0.435***	0.482***
	(0.030)	(0.035)	(0.043)	(0.039)	(0.041)	(0.047)
F-stat	141.38	146.93	100.46	76.30	67.43	53.22
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Sample	Full	Full	Full	Full	MSE	MSE
Polynomial Forcing variable	First	First	Second	Second	First	First
Interaction term	Yes	Yes	Yes	Yes	Yes	Yes
Departmental ranking FE	Yes	Yes	Yes	Yes	Yes	Yes
Year of application FE	Yes	Yes	Yes	Yes	Yes	Yes
Year of graduation FE	Yes	Yes	Yes	Yes	Yes	Yes
Student characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Parent characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,657	2,178	1,657	2,178	923	1,343
R-squared	0.116	0.130	0.001	0.127	0.129	0.142

Notes. Fuzzy RDD estimates. The outcome variable is reported at the top of each column. In odd columns, we focus on the sample of Bachelor students and, in even columns, on the sample of Master students. In specifications (1) and (2), we control for a first-order polynomial of the assignment variable and for a first-order interaction term between the treatment and the ranking score for the full sample. In specifications (3) and (4), we add a second-order polynomial of the assignment variable along with a second-order interaction term. In specifications (5) and (6), we implement a LLR within the MSE-optimal bandwidth. Standard errors are robust to heteroskedasticity and clustered at the departmental ranking level (reported inside the brackets). Significance at the 10 percent level is represented by *, at the 5 percent level by **, and at the 1 percent level by ***.

Table 8: Erasmus program and the probability of employment by field of study. Fuzzy RDD estimates.

	(1)	(2)	(3)	(4)	(5)	(6)
	Employed	Employed	Employed	Employed	Employed	Employed
	STEM	Other	STEM	Other	STEM	Other
			Panel (a): 2SLS			
Erasmus	0.220***	0.122**	0.231***	-0.013	0.241*	0.098
	(0.066)	(0.056)	(0.078)	(0.073)	(0.136)	(0.092)
			Panel (b): First stage			
Assigned Erasmus	0.576***	0.487***	0.549***	0.468***	0.478***	0.464***
	(0.038)	(0.028)	(0.042)	(0.036)	(0.049)	(0.039)
F-stat	121.74	151.14	78.56	89.36	53.58	90.85
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Sample	Full	Full	Full	Full	MSE	MSE
Polynomial Forcing variable	First	First	Second	Second	First	First
Interaction term	Yes	Yes	Yes	Yes	Yes	Yes
Departmental ranking FE	Yes	Yes	Yes	Yes	Yes	Yes
Year of application FE	Yes	Yes	Yes	Yes	Yes	Yes
Year of graduation FE	Yes	Yes	Yes	Yes	Yes	Yes
Student characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Parent characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,630	2,205	1,630	2,205	953	1,313
R-squared	0.272	0.138	0.271	0.129	0.333	0.161

Notes. Fuzzy RDD estimates. The outcome variable is reported at the top of each column. In odd columns, we focus on the sample of STEM students and, in even columns, on students enrolled in a different degree. In specifications (1) and (2), we control for a first-order polynomial of the assignment variable and for a first-order interaction term between the treatment and the ranking score for the full sample. In specifications (3) and (4), we add a second-order polynomial of the assignment variable along with a second-order interaction term. In specifications (5) and (6), we implement a LLR within the MSE-optimal bandwidth. Standard errors are robust to heteroskedasticity and clustered at the departmental ranking level (reported inside the brackets). Significance at the 10 percent level is represented by *, at the 5 percent level by **, and at the 1 percent level by ***.

Table 9: Intention-To-Treat analysis. Sharp RDD estimates

	(1) Employed	(2) Employed	(3) Employed	(4) Time to find a job	(5) Time to find a job	(6) Time to find a job	(7) Job in line with studies	(8) Job in line with studies	(9) Job in line with studies
Panel (a): 2SLS									
Assigned Erasmus	0.083***	0.050	0.072*	-1.192***	-1.338***	-0.777	0.013	-0.060	0.063
	(0.025)	(0.030)	(0.037)	(0.372)	(0.454)	(0.519)	(0.048)	(0.060)	(0.086)
Sample	Full	Full	MSE	Full	Full	MSE	Full	Full	MSE
Polynomial Forcing variable	First	Second	First	First	Second	First	First	Second	First
Interaction term	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Departmental ranking FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year of application FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year of graduation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Student characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parent characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,835	3,835	2,266	1,091	1,091	749	1,101	1,101	496
R-squared	0.208	0.208	0.249	0.172	0.172	0.241	0.117	0.120	0.240

Notes. Sharp RDD estimates. The outcome variable is reported at the top of each column. In columns (1), (4) and (7), we control for a first-order polynomial of the assignment variable and for a first-order interaction term between the treatment and the ranking score for the full sample. In columns (2) , (5) and (8), we add a second-order polynomial of the assignment variable along with a second-order interaction term. In columns (3), (6) and (9), we implement a LLR within the MSE-optimal bandwidth. Standard errors are robust to heteroskedasticity and clustered at the departmental ranking level (reported inside the brackets). Significance at the 10 percent level is represented by *, at the 5 percent level by **, and at the 1 percent level by ***.

Table 10: Erasmus program, proficiency in English and mobility propensity. Fuzzy RDD estimates. LLR with MSE-bandwidth

	(1) Written English	(2) Oral English	(3) Work in Europe	(4) Work outside Europe
Panel (a): 2SLS				
Erasmus	0.055	0.108*	0.381**	0.025
	(0.056)	(0.064)	(0.186)	(0.139)
Female	0.003	0.024	-0.092***	-0.042
	(0.019)	(0.023)	(0.044)	(0.038)
High-school grade	0.005***	0.005***	0.005**	-0.001
	(0.001)	(0.001)	(0.002)	(0.002)
Age	0.006*	0.010**	0.008	0.003
	(0.004)	(0.004)	(0.014)	(0.011)
Lyceum	-0.002	0.028	0.003	0.075*
	(0.020)	(0.024)	(0.048)	(0.042)
Province of residence	-0.025	0.004	-0.018	-0.004
	(0.018)	(0.020)	(0.062)	(0.042)
Parental education	0.046***	0.037*	0.020	0.030
	(0.017)	(0.022)	(0.040)	(0.032)
Panel (b): First stage				
Assigned Erasmus	0.470***	0.463***	0.375***	0.409***
	(0.033)	(0.039)	(0.054)	(0.047)
F-stat	111.28	94.46	38.02	60.64
p-value	0.000	0.000	0.000	0.000
Optimal bandwidth	MSE	MSE	MSE	MSE
Polynomial Forcing variable	First	First	First	First
Interaction term	Yes	Yes	Yes	Yes
Departmental ranking FE	Yes	Yes	Yes	Yes
Year of application FE	Yes	Yes	Yes	Yes
Year of graduation FE	Yes	Yes	Yes	Yes
Student characteristics	Yes	Yes	Yes	Yes
Parent characteristics	Yes	Yes	Yes	Yes
Observations	1,954	1,833	572	864
R-squared	0.089	0.073	0.127	0.106

Notes. Fuzzy RDD estimates. The outcome variable is reported at the top of each column. In all specifications, we implement a LLR within the MSE-optimal bandwidth. Standard errors are robust to heteroskedasticity and clustered at the departmental ranking level (reported inside the brackets). Significance at the 10 percent level is represented by *, at the 5 percent level by **, and at the 1 percent level by ***.

Table 11: Erasmus program and educational outcomes. Fuzzy RDD estimates. LLR with MSE-bandwidth

	(1) Graduation grade	(2) Distinction	(3) Additional years to graduate
	Panel (a): 2SLS		
Erasmus	2.478***	0.122	0.121
	(0.834)	(0.080)	(0.167)
Female	0.252	0.024	-0.058
	(0.267)	(0.018)	(0.047)
High-school grade	0.194***	0.010***	-0.001
	(0.018)	(0.001)	(0.002)
Age	0.891***	0.034***	0.003
	(0.074)	(0.007)	(0.015)
Lyceum	-0.813***	-0.075***	0.026
	(0.276)	(0.022)	(0.045)
Province of residence	0.259	0.052***	-0.021
	(0.251)	(0.020)	(0.035)
Parental education	-0.091	0.001	-0.023
	(0.229)	(0.018)	(0.045)
	Panel (b): First stage		
Assigned Erasmus	0.459***	0.468***	0.442***
	(0.039)	(0.033)	(0.040)
F-stat	93.61	112.96	74.26
p-value	0.000	0.000	0.000
Optimal bandwidth	MSE	MSE	MSE
Polynomial Forcing variable	First	First	First
Interaction term	Yes	Yes	Yes
Departmental ranking FE	Yes	Yes	Yes
Year of application FE	Yes	Yes	Yes
Year of graduation FE	Yes	Yes	Yes
Student characteristics	Yes	Yes	Yes
Parent characteristics	Yes	Yes	Yes
Observations	1,794	1,960	1,646
R-squared	0.404	0.181	0.469

Notes. Fuzzy RDD estimates within the MSE-optimal bandwidth. The outcome variable is reported at the top of each column. In every specification, we control for a first-order polynomial of the assignment variable and for a first-order interaction term between the treatment and the ranking score. Standard errors are robust to heteroskedasticity and clustered at the departmental ranking level (reported inside the brackets). Significance at the 10 percent level is represented by *, at the 5 percent level by **, and at the 1 percent level by ***.

Table 12: Erasmus program and educational outcomes by quality of host institution. Fuzzy RDD estimates. LLR with MSE-bandwidth

	(1) Graduation grade	(2) Graduation grade	(3) Distinction	(4) Distinction	(5) Additional years to graduate	(6) Additional years to graduate
	High-quality	Lower quality	High-quality	Lower quality	High-quality	Lower quality
	Panel (a): 2SLS					
Erasmus	12.43**	2.354*	0.070	0.087	-0.191	0.116
	(5.893)	(1.275)	(0.711)	(0.121)	(1.268)	(0.218)
Female	-0.122	0.200	0.032	0.022	-0.105*	-0.028
	(0.465)	(0.365)	(0.036)	(0.021)	(0.056)	(0.053)
High-school grade	0.171***	0.196***	0.010***	0.009***	0.002	-0.002
	(0.027)	(0.022)	(0.002)	(0.001)	(0.003)	(0.003)
Age	0.847***	0.937***	0.027***	0.033***	-0.002	0.001
	(0.103)	(0.077)	(0.010)	(0.007)	(0.015)	(0.014)
Lyceum	-0.796**	-0.913***	-0.076**	-0.086***	0.071	-0.020
	(0.330)	(0.294)	(0.030)	(0.023)	(0.055)	(0.051)
Province of residence	0.243	0.155	0.104**	0.039*	0.055	-0.042
	(0.559)	(0.322)	(0.043)	(0.023)	(0.072)	(0.034)
Parental education	-0.397	-0.058	-0.004	0.006	-0.009	-0.034
	(0.357)	(0.271)	(0.032)	(0.022)	(0.063)	(0.046)
	Panel (b): First stage					
Assigned Erasmus	0.090***	0.352***	0.088***	0.357***	0.083***	0.352***
	(0.025)	(0.040)	(0.024)	(0.035)	(0.026)	(0.041)
F-stat	8.46	71.11	8.71	77.03	7.20	56.43
p-value	0.000	0.000	0.000	0.000	0.002	0.000
Optimal bandwidth	MSE	MSE	MSE	MSE	MSE	MSE
Polynomial Forcing variable	First	First	First	First	First	First
Interaction term	Yes	Yes	Yes	Yes	Yes	Yes
Departmental ranking FE	Yes	Yes	Yes	Yes	Yes	Yes
Year of application FE	Yes	Yes	Yes	Yes	Yes	Yes
Year of graduation FE	Yes	Yes	Yes	Yes	Yes	Yes
Student characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Parent characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,224	1,530	1,350	1,681	1,112	1,395
R-squared	0.392	0.415	0.001	0.168	0.022	0.402

Notes. Fuzzy RDD estimates. The outcome variable is reported at the top of each column. In odd columns, we focus on the sample of students who studied abroad in a high-quality institution and, in even columns, on the sample of students who studied abroad in a lower quality institution. In all specifications, we implement a LLR within the MSE-optimal bandwidth. Standard errors are robust to heteroskedasticity and clustered at the departmental ranking level (reported inside the brackets). Significance at the 10 percent level is represented by *, at the 5 percent level by **, and at the 1 percent level by ***.

Table 13: Erasmus program and educational outcomes by months spent abroad. Fuzzy RDD estimates. LLR with MSE-bandwidth

	(1) Graduation grade	(2) Graduation grade	(3) Distinction	(4) Distinction	(5) Additional years to graduate	(6) Additional years to graduate
	$\leq$ 5 months	$>$ 5 months	$\leq$ 5 months	$>$ 5 months	$\leq$ 5 months	$>$ 5 months
Panel (a): 2SLS						
Erasmus	2.897**	7.902*	0.129	0.373	0.147	-0.003
	(1.235)	(4.725)	(0.106)	(0.411)	(0.220)	(0.701)
Female	0.336	-0.245	0.026	0.016	-0.056	-0.077
	(0.276)	(0.420)	(0.019)	(0.023)	(0.050)	(0.060)
High-school grade	0.198***	0.173***	0.009***	0.010***	-0.001	-0.001
	(0.019)	(0.022)	(0.001)	(0.001)	(0.003)	(0.003)
Age	0.885***	0.877***	0.031***	0.028***	0.010	0.008
	(0.073)	(0.090)	(0.007)	(0.008)	(0.015)	(0.014)
Lyceum	-0.828***	-0.863***	-0.071***	-0.080***	0.031	0.043
	(0.278)	(0.327)	(0.022)	(0.029)	(0.049)	(0.060)
Province of residence	0.274	0.247	0.044**	0.050*	-0.012	-0.087*
	(0.256)	(0.361)	(0.020)	(0.027)	(0.037)	(0.048)
Parental education	-0.036	-0.188	0.004	0.002	-0.022	0.010
	(0.253)	(0.330)	(0.020)	(0.025)	(0.047)	(0.063)
Panel (b): First stage						
Assigned Erasmus	0.371***	0.116***	0.384***	0.116***	0.352***	0.120***
	(0.046)	(0.026)	(0.040)	(0.025)	(0.046)	(0.029)
F-stat	46.02	12.98	54.13	16.56	40.95	12.51
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Optimal bandwidth	MSE	MSE	MSE	MSE	MSE	MSE
Polynomial Forcing variable	First	First	First	First	First	First
Interaction term	Yes	Yes	Yes	Yes	Yes	Yes
Departmental ranking FE	Yes	Yes	Yes	Yes	Yes	Yes
Year of application FE	Yes	Yes	Yes	Yes	Yes	Yes
Year of graduation FE	Yes	Yes	Yes	Yes	Yes	Yes
Student characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Parent characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,644	1,249	1,795	1,380	1,508	1,134
R-squared	0.403	0.408	0.163	0.012	0.446	0.296

Notes. Fuzzy RDD estimates. The outcome variable is reported at the top of each column. In odd columns, we focus on the sample of students who studied abroad less than 5 months and, in even columns, on the sample of students who studied abroad more than 5 months. In all specifications, we implement a LLR within the MSE-optimal bandwidth. Standard errors are robust to heteroskedasticity and clustered at the departmental ranking level (reported inside the brackets). Significance at the 10 percent level is represented by *, at the 5 percent level by **, and at the 1 percent level by ***.

Appendix

Table A1: Erasmus program and further labour market outcomes by gender. Fuzzy RDD estimates. LLR with MSE-bandwidth

	(1) Time to find a job	(2) Time to find a job	(3) Job in line with studies	(4) Job in line with studies
	Female	Male	Female	Male
Panel (a): 2SLS				
Erasmus	-0.761	-1.844	-0.143	0.853
	(1.663)	(1.433)	(0.233)	(0.525)
Panel (b): First stage				
Assigned Erasmus	0.435***	0.571***	0.497***	0.362***
	(0.078)	(0.081)	(0.136)	(0.104)
F-stat	17.15	26.32	8.23	7.75
p-value	0.000	0.000	0.000	0.001
Optimal bandwidth	MSE	MSE	MSE	MSE
Polynomial Forcing variable	First	First	First	First
Interaction term	Yes	Yes	Yes	Yes
Departmental ranking FE	Yes	Yes	Yes	Yes
Year of application FE	Yes	Yes	Yes	Yes
Year of graduation FE	Yes	Yes	Yes	Yes
Student characteristics	Yes	Yes	Yes	Yes
Parent characteristics	Yes	Yes	Yes	Yes
Observations	368	381	264	232
R-squared	0.254	0.334	0.325	

Notes. Fuzzy RDD estimates. The outcome variable is reported at the top of each column. In odd columns, we focus on the sample of female students and, in even columns, on the sample of male students. In all specifications, we implement a LLR within the MSE-optimal bandwidth. Standard errors are robust to heteroskedasticity and clustered at the departmental ranking level (reported inside the brackets). Significance at the 10 percent level is represented by *, at the 5 percent level by **, and at the 1 percent level by ***.

Table A2: Erasmus program and further labour market outcomes by Bachelor/Master graduates. Fuzzy RDD estimates. LLR with MSE-bandwidth

	(1) Time to find a job	(2) Time to find a job	(3) Job in line with studies	(4) Job in line with studies
	Bachelor	Master	Bachelor	Master
	Panel (a): 2SLS			
Erasmus	-4.539*	-1.192	-0.329	0.209
	(2.650)	(1.270)	(0.558)	(0.219)
	Panel (b): First stage			
Assigned Erasmus	0.515**	0.509***	0.359	0.474***
	(0.185)	(0.062)	(0.346)	(0.100)
F-stat	8.10	35.92	1.85	12.70
p-value	0.002	0.000	0.177	0.000
Optimal bandwidth	MSE	MSE	MSE	MSE
Polynomial Forcing variable	First	First	First	First
Interaction term	Yes	Yes	Yes	Yes
Departmental ranking FE	Yes	Yes	Yes	Yes
Year of application FE	Yes	Yes	Yes	Yes
Year of graduation FE	Yes	Yes	Yes	Yes
Student characteristics	Yes	Yes	Yes	Yes
Parent characteristics	Yes	Yes	Yes	Yes
Observations	142	607	113	383
R-squared	0.151	0.269	0.192	0.261

Notes. Fuzzy RDD estimates. The outcome variable is reported at the top of each column. In odd columns, we focus on the sample of Bachelor students and, in even columns, on the sample of Master students. In all specifications, we implement a LLR within the MSE-optimal bandwidth. Standard errors are robust to heteroskedasticity and clustered at the departmental ranking level (reported inside the brackets). Significance at the 10 percent level is represented by *, at the 5 percent level by **, and at the 1 percent level by ***.

Table A3: Erasmus program and further labour market outcomes by field of study. Fuzzy RDD estimates. LLR with MSE-bandwidth

	(1) Time to find a job	(2) Time to find a job	(3) Job in line with studies	(4) Job in line with studies
	STEM	Other	STEM	Other
Panel (a): 2SLS				
Erasmus	-2.018**	-1.460	0.335*	-0.075
	(0.973)	(2.398)	(0.177)	(0.342)
Panel (b): First stage				
Assigned Erasmus	0.604***	0.372***	0.624***	0.332***
	(0.050)	(0.091)	(0.109)	(0.117)
F-stat	109.96	10.34	26.02	6.69
p-value	0.000	0.000	0.000	0.003
Optimal bandwidth	MSE	MSE	MSE	MSE
Polynomial Forcing variable	First	First	First	First
Interaction term	Yes	Yes	Yes	Yes
Departmental ranking FE	Yes	Yes	Yes	Yes
Year of application FE	Yes	Yes	Yes	Yes
Year of graduation FE	Yes	Yes	Yes	Yes
Student characteristics	Yes	Yes	Yes	Yes
Parent characteristics	Yes	Yes	Yes	Yes
Observations	380	369	194	302
R-squared	0.248	0.235		0.307

Notes. Fuzzy RDD estimates. The outcome variable is reported at the top of each column. In odd columns, we focus on the sample of STEM students and, in even columns, on students enrolled in a different degree. In all specifications, we implement a LLR within the MSE-optimal bandwidth. Standard errors are robust to heteroskedasticity and clustered at the departmental ranking level (reported inside the brackets). Significance at the 10 percent level is represented by *, at the 5 percent level by **, and at the 1 percent level by ***.

Table A4: Erasmus program and educational outcomes by gender. Fuzzy RDD estimates. LLR with MSE-bandwidth

	(1) Graduation grade	(2) Graduation grade	(3) Distinction	(4) Distinction	(5) Additional years to graduate	(6) Additional years to graduate
	Female	Male	Female	Male	Female	Male
			Panel (a): 2SLS			
Erasmus	1.723	2.873**	0.003	0.230**	-0.091	0.299
	(1.187)	(1.336)	(0.090)	(0.111)	(0.219)	(0.212)
			Panel (b): First stage			
Assigned Erasmus	0.424***	0.515***	0.445***	0.501***	0.418***	0.488***
	(0.043)	(0.057)	(0.040)	(0.044)	(0.046)	(0.061)
F-stat	65.37	55.09	76.16	70.31	56.59	37.05
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Optimal bandwidth	MSE	MSE	MSE	MSE	MSE	MSE
Polynomial Forcing variable	First	First	First	First	First	First
Interaction term	First	Yes	Yes	Yes	Yes	Yes
Yes						
Departmental ranking FE	Yes	Yes	Yes	Yes	Yes	Yes
Year of application FE	Yes	Yes	Yes	Yes	Yes	Yes
Year of graduation FE	Yes	Yes	Yes	Yes	Yes	Yes
Student characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Parent characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	987	807	1,072	888	908	738
R-squared	0.425	0.447	0.261	0.115	0.530	0.453

Notes. Fuzzy RDD estimates. The outcome variable is reported at the top of each column. In odd columns, we focus on the sample of female students and, in even columns, on the sample of male students. In all specifications, we implement a LLR within the MSE-optimal bandwidth. Standard errors are robust to heteroskedasticity and clustered at the departmental ranking level (reported inside the brackets). Significance at the 10 percent level is represented by *, at the 5 percent level by **, and at the 1 percent level by ***.

Table A5: Erasmus program and educational outcomes by field of study. Fuzzy RDD estimates. LLR with MSE-bandwidth

	(1) Graduation grade	(2) Graduation grade	(3) Distinction	(4) Distinction	(5) Additional years to graduate	(6) Additional years to graduate
	STEM	Other	STEM	Other	STEM	Other
			Panel (a): 2SLS			
Erasmus	3.398***	1.531	0.180	0.082	0.068	0.195
	(1.168)	(1.190)	(0.113)	(0.105)	(0.151)	(0.273)
			Panel (b): First stage			
Assigned Erasmus	0.503***	0.420***	0.491***	0.442***	0.463***	0.419***
	(0.068)	(0.045)	(0.055)	(0.040)	(0.072)	(0.047)
F-stat	29.27	85.33	47.06	95.40	23.13	67.05
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Optimal bandwidth	MSE	MSE	MSE	MSE	MSE	MSE
Polynomial Forcing variable	First	First	First	First	First	First
Interaction term	Yes	Yes	Yes	Yes	Yes	Yes
Departmental ranking FE	Yes	Yes	Yes	Yes	Yes	Yes
Year of application FE	Yes	Yes	Yes	Yes	Yes	Yes
Year of graduation FE	Yes	Yes	Yes	Yes	Yes	Yes
Student characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Parent characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	740	1,054	809	1,151	680	966
R-squared	0.403	0.401	0.151	0.212	0.575	0.421

Notes. Fuzzy RDD estimates. The outcome variable is reported at the top of each column. In odd columns, we focus on the sample of STEM students and, in even columns, on students enrolled in a different degree. In all specifications, we implement a LLR within the MSE-optimal bandwidth. Standard errors are robust to heteroskedasticity and clustered at the departmental ranking level (reported inside the brackets). Significance at the 10 percent level is represented by *, at the 5 percent level by **, and at the 1 percent level by ***.

Table A6: Erasmus program and labour market outcomes by quality of institutions. Fuzzy RDD estimates. LLR with MSE-bandwidth

	(1) Employed	(2) Employed	(3) Time to find ajob	(4) Time to find a job	(5) Job in line with studies	(6) Job in line with studies
	High-quality	Lower quality	High-quality	Lower quality	High-quality	Lower quality
			Panel (a): 2SLS			
Erasmus	0.823	0.169*	3.150	-2.034	0.487	0.277
	(0.544)	(0.101)	(7.479)	(1.616)	(1.469)	(0.323)
			Panel (b): First stage			
Assigned Erasmus	0.083***	0.358***	0.129**	0.350***	0.114*	0.290***
	(0.022)	(0.033)	(0.052)	(0.067)	(0.058)	(0.091)
F-stat	10.52	72.63	4.89	16.95	2.92	5.66
p-value	0.000	0.000	0.011	0.000	0.062	0.006
Optimal bandwidth	MSE	MSE	MSE	MSE	MSE	MSE
Polynomial Forcing variable	First	First	First	First	First	First
Interaction term	Yes	Yes	Yes	Yes	Yes	Yes
Departmental ranking FE	Yes	Yes	Yes	Yes	Yes	Yes
Year of application FE	Yes	Yes	Yes	Yes	Yes	Yes
Year of graduation FE	Yes	Yes	Yes	Yes	Yes	Yes
Student characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Parent characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,581	1,950	508	618	325	409
R-squared	0.199	0.233		0.249		0.181

Notes. Fuzzy RDD estimates. The outcome variable is reported at the top of each column. In odd columns, we focus on the sample of students who studied abroad in a high-quality institution and, in even columns, on the sample of students who studied abroad in a low-quality institution. In all specifications, we implement a LLR within the MSE-optimal bandwidth. Standard errors are robust to heteroskedasticity and clustered at the departmental ranking level (reported inside the brackets). Significance at the 10 percent level is represented by *, at the 5 percent level by **, and at the 1 percent level by ***.

Table A7: Erasmus program and labour market outcomes by months spent abroad. Fuzzy RDD estimates. LLR with MSE-bandwidth

	(1) Employed	(2) Employed	(3) Time to find ajob	(4) Time to find a job	(5) Job in line with studies	(6) Job in line with studies
	$\leq$ 5 months	> 5 months	$\leq$ 5 months	> 5 months	$\leq$ 5 months	> 5 months
Panel (a): 2SLS						
Erasmus	0.179*	0.616*	-1.184	-5.442	0.042	0.796
	(0.106)	(0.351)	(1.378)	(5.282)	(0.211)	(0.717)
Panel (b): First stage						
Assigned Erasmus	0.382***	0.124***	0.394***	0.177***	0.392***	0.175**
	(0.036)	(0.025)	(0.062)	(0.045)	(0.090)	(0.075)
F-stat	62.36	18.03	22.73	9.33	13.58	4.67
p-value	0.000	0.000	0.000	0.000	0.000	0.013
Optimal bandwidth	MSE	MSE	MSE	MSE	MSE	MSE
Polynomial Forcing variable	First	First	First	First	First	First
Interaction term	Yes	Yes	Yes	Yes	Yes	Yes
Departmental ranking FE	Yes	Yes	Yes	Yes	Yes	Yes
Year of application FE	Yes	Yes	Yes	Yes	Yes	Yes
Year of graduation FE	Yes	Yes	Yes	Yes	Yes	Yes
Student characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Parent characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,086	1,614	686	513	455	342
R-squared	0.240	0.212	0.230		0.212	0.020

Notes. Fuzzy RDD estimates. The outcome variable is reported at the top of each column. In odd columns, we focus on the sample of students who studied abroad less than 5 months and, in even columns, on the sample of students who studied abroad more than 5 months. In all specifications, we implement a LLR within the MSE-optimal bandwidth. Standard errors are robust to heteroskedasticity and clustered at the departmental ranking level (reported inside the brackets). Significance at the 10 percent level is represented by *, at the 5 percent level by **, and at the 1 percent level by ***.